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Developmental Profiles of 57,966 Children in Early Intervention: A Confirmatory Latent Profile Analysis

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DEVELOPMENTAL PROFILES OF 57,966 CHILDREN IN EARLY INTERVENTION: A CONFIRMATORY LATENT PROFILE ANALYSIS

A Thesis Presented

by

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ABSTRACT

DEVELOPMENTAL PROFILES OF 57,966 CHILDREN IN EARLY INTERVENTION: A CONFIRMATORY LATENT PROFILE ANALYSIS

May 2021

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Part C Early Intervention, which is a state and federally funded nationwide program, seeks to support children ages zero to three years old who demonstrate delays in developmental functioning or who are at-risk for developmental delays. The Battelle Developmental Inventory, Second Edition (BDI-2) is frequently used in Early Intervention (EI) to assess the developmental functioning of children across five domains—Communicative, Cognitive, Motor, Adaptive and Personal/Social—yet relatively little is known about child developmental profiles based on these domain scores. This study aimed to replicate and extend findings from the only known study (Elbaum & Celimli-Aksoy, 2017) that has conducted a latent profile analysis of child developmental profiles measured by the BDI-2 for children in Part C EI. The current study includes children (N=57,966) who were enrolled in one of twelve Part C EI agencies in the state of Massachusetts between 2011-2019 and completed a BDI-2 assessment at entry to EI. Findings suggest that the data is best classified into four latent classes, replicating findings of Elbaum et al (2017). Furthermore, and more notably, the pattern of BDI-2 scores (domain means for each class) found in Elbaum et al. (2017) was replicated in this study. This study extends previous findings by describing the extent to which child characteristics (sociodemographic factors, ASD diagnosis) predict class membership. Results show that for most class comparisons, demographic factors significantly predicted class membership. The effects of age and ASD diagnosis were particularly large in the prediction of class membership. Our results suggest that 1) Battelle developmental profiles could be an additional indicator to improve identification of ASD risk in community settings and 2) profile membership could guide streamlined but person-oriented service receipt by tailoring interventions to specific child developmental needs. Continued research is needed to determine if profile membership is consistent across time and age.

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CHAPTER 1

BACKGROUND AND SIGNIFICANCE

The prevalence of developmental disabilities, such as global developmental delay and autism, in children is high; data from 2009-2017 shows that about 1 in 6 children in the U.S. has a diagnosed developmental disability and this rate has increased over time (Zablotsky et al., 2019). Access to early intervention services from a young age can support child development, facilitate assessment and identification of developmental disabilities, and help prevent further developmental delays. Through Part C of the Individuals with Disabilities Education Act (IDEA) children, ages zero to three, with a developmental delay or specific health condition (e.g., hearing loss) can enroll in state and federally funded Early Intervention (EI) programs. EI programs provide an array of services such as speech therapy, physical therapy, occupational therapy, and parent coaching in both home and community settings. EI services are offered in every state and U.S. territory. In 2018, approximately 389,000 children nationwide, or 3.1% of the population under 3 years of age, were enrolled in a Part C EI program (Lazara, 2019; Keating et al., 2019). While eligibility requirements vary by state, nationwide children qualify for EI services by demonstrating deficits or delays in developmental functioning. Children are also eligible for services if they belong to a group particularly at-risk for developmental delays (e.g., low birth weight, drug exposure, genetic conditions). The present study focused on understanding patterns in the developmental profiles of infants and toddlers in EI by statistically exploring an assessment that is widely used to characterize child developmental functioning.

Battelle Developmental Inventory (BDI)

The Battelle Developmental inventory (BDI; Newborg, Stock, Wnek, Guidubaldi, & Svinicki, 1984; BDI-2, Newborg, 2005) is a commonly used assessment that measures a child's developmental level and fulfills eligibility and monitoring requirements mandated by many states (Stone-MacDonald, Pizzo, & Feldman, 2018). A norm-referenced assessment for children between the ages of 0 and 7 years 11 months, the Battelle Developmental Inventory assesses 5 domains of development—communication, adaptive, motor, cognitive, personal/social—and includes a variety of formats—observation, structured administration, parent interview.

Evidence to support the utility and psychometric soundness of the Battelle Developmental Inventory in EI is variable. Early evaluations of the first edition of the Battelle Developmental Inventory (BDI; Newborg et al., 1984) indicated the measure had strong psychometric properties, including for children ages 0 to 30 months (McLean et al., 1987). However, the second of edition of the Battelle Developmental Inventory (BDI-2; Newborg, 2005) has not been independently evaluated for its psychometric properties (Cunha et al., 2018). Data from the examiner's manual (Newborg, 2016; Newborg, 2005) and interpretations of this data (Alfonso et al., 2010; Bliss, 2007) conclude that the BDI-2 has displayed strong psychometric properties including interrater reliability (greater than 0.80 for all domains). Cunha and colleagues (2018) emphasize however that independent studies, using data other than that collected by authors of the measure, that investigate the reliability and validity of the BDI-2 are lacking. Despite evidence suggesting that more research is needed on the psychometric properties of the BDI-2, the present study uses it as the primary measure of child developmental functioning.

Importantly, the BDI-2 is very frequently used for developmental assessment in the Early Intervention system. A nationwide study that surveyed 969 providers from 22 different states found that a majority (range: 65.9 - 76.4%) of EI providers reported using the BDI-2 for a variety of purposes including: a) deciding eligibility for early intervention or special education, b) creating Individualized Family Service Plans (IFSPs) or Individualized Education Plans (IEPs), c) planning intervention activities, and d) following a child's progress (Lee et al., 2016). The widespread use of the BDI-2 is likely due to requirements put forth by states. For example, the state of Massachusetts, which is the EI setting for this study, requires that the Battelle Developmental be used "to establish eligibility by delay for all children entering the system (pg. 11, Massachusetts Department of Public Health, 2013). Thus, while more evidence for the reliability and validity of the BDI-2 is needed, the widespread and mandated use of it in community-based settings across multiple states justify this study and its aims to identify developmental profiles of children, using scores obtained through the BDI-2.

Developmental profiles using the BDI

In addition to clinical applications, researchers commonly use standardized assessments to explore developmental or cognitive profiles of children. For example, numerous studies of the Weschler Intelligence Scale for Children (WISC, Wechsler, 1991, 2003) have used profile or cluster analysis to determine if children with certain genetic or developmental disorders have unique WISC profiles, as measured by its four subscales (e.g. Thaler, Bello, & Etcoff, 2013; Zander & Dahlgren, 2010).

The identification of distinct cognitive or developmental profiles is justified by the possibility of these profiles facilitating better tailored treatments and supports for individuals with developmental delays. A few recent studies have investigated the association between clinical diagnosis or symptoms and developmental profiles, as measured by the BDI-2. One small study with 28 toddlers ages 17-34 months (Matson et al., 2010) compared developmental profiles, using the five domains of the BDI-2, based on their existing clinical diagnoses of Down Syndrome, Global Developmental Delay or preterm birth status. Results showed that children with Down Syndrome and Global Developmental Delay not only scored lower overall on the BDI-2 but scored lower on two specific domains in particular, as compared to children born premature. Similarly, Shevell and colleagues (2005) compared overall BDI scores of school-aged children who had been previously diagnosed with global developmental delay (GDD; N=48) or developmental language impairment (DLI; N=43) in preschool. Measured by the overall composite score of the BDI, children with GDD showed significantly greater impairment as compared to children with DLI (p=.002) approximately 4 years after their original diagnosis. Findings from these studies provide preliminary evidence of differential developmental profiles and trajectories based on a child's clinical presentation or diagnosis, suggesting that there may be meaningful subgroups of children in terms of their developmental functioning that can be identified based on their BDI-2 scores.

Another study investigated whether the BDI-2 could be used as a screener for Autism Spectrum Disorder (ASD). The authors sought to establish a cut-off score for the overall composite BDI-2 score which could serve as an indicator of ASD risk (Sipes et al., 2011). The study compared two groups of children in EI: those who were identified as meeting criteria for ASD and those who did not meet criteria for ASD. Children with ASD had an average overall score of 75.4 (SD=14.0) on the BDI-2, whereas children who did not meet criteria for ASD had an average overall score of 90.0 (SD=13.4). A cut-off score of 96 and below on the BDI-2, which is 1.5 standard deviations from the ASD group mean, was identified as an indicator of ASD risk with high sensitivity, (0.94) but a rather low specificity (0.31).

Rather than only evaluating the overall composite score provided by a BDI-2 assessment, Goldin and colleagues (2014) explored the association between ASD symptom severity, measured by the Baby and Infant Screen for Children with aUtIsm Traits- Part 1, and the five BDI-2 domains scores for children ages 17-36 months in EI who had existing diagnoses of ASD. Not only did higher ASD symptom severity predict lower overall composite scores—indicating more impairment—on the BDI-2, but ASD symptom severity also significantly predicted scores on each of the five domains over and above the total composite score. Higher ASD severity most strongly predicted lower scores on the personal-social domain of the BDI-2 followed by adaptive, cognitive, motor and communicative domains, respectively. While the findings are significant, the effect sizes lie in the small range (partial eta^2=0.07-.16). The findings of this study suggest that children with ASD diagnoses may demonstrate heterogeneous BDI-2 profiles, and this may be due to their ASD symptom severity. Another study investigated the relationship between composite as well as domain BDI-2 scores and challenging behaviors for 1,509 toddlers diagnosed with ASD, pervasive developmental disorder-not otherwise specified (PDD-NOS) or atypically developing children with no ASD diagnosis who were enrolled in a Part C Early Intervention program (Medeiros et al., 2012). By conducting multiple regression analyses, researchers found that for children with an ASD or PDD-NOS diagnosis, a higher overall BDI-2 composite score was significantly associated with a higher incidence of challenging behaviors. Conversely, for atypically developing children who had no ASD diagnosis, a higher composite score was significantly associated with fewer challenging behaviors. Furthermore, there were differential effects of the domains on particular challenging behaviors and this varied by child diagnosis. For example, children diagnosed with ASD showed higher aggressive/destructive challenging behaviors with greater motor skills, as measured by the BDI-2, compared to the other two groups of children. The authors conclude that since the relationship between diagnosis and developmental skills of a child uniquely impact his or her externalizing behaviors, specific intervention strategies should consider information provided by BDI-2 domain scores, not only diagnosis. Taken together, these two studies suggest that understanding the unique BDI-2 developmental profiles of children with ASD, by investigating their domain scores, could provide clinically useful information and lead to more individualized and tailored services in EI.

Despite the widespread use of the BDI-2 in the early intervention setting, relatively little is known about child developmental profiles based on its five domain scores, without using prior diagnosis as a grouping variable. Only one study to date has used mixture modeling to uncover latent profiles of children (N=1,513) enrolled in Part C EI services based on their BDI-2 domain scores (Elbaum & Celimli-Aksoy, 2017). Analyses revealed four latent classes. Two classes show large discrepancies between communication, cognitive and motor domains; of these two classes, one shows relatively greater delays than the other. Two classes show somewhat level scores between communication, cognitive and motor domains; of these two classes, one shows relatively greater delays than the other. Children in the two classes with large discrepancies between communication, cognitive and motor domains were more likely to fall into the category "suspected ASD," while children with level scores across these three domains were primarily identified as having "developmental delays" or "established conditions." Results of this study suggest not only that unique developmental profiles based on BDI-2 domains exist, but also that profiles may provide useful information about the risk for a specific type of developmental disability, like autism, based on a child's class membership.

Elbaum and colleagues (2017) caution against broadly generalizing a singular developmental profile as indicative of ASD because while a majority of children with "suspected ASD" showed primary delays in the communication domain, a minority (8%) showed global delays across all domains. Thus, children who are in the same diagnostic category may have dissimilar profiles. It may be that different levels of ASD severity result in disparate developmental profiles, as measured by the BDI-2; Goldin et al. (2014) found that the severity of ASD symptoms predicted BDI-2 domains scores. In this study it is expected that some developmental profiles will be more strongly associated with ASD, as evidenced by a higher percentage of members diagnosed with ASD and that there will also likely be variation in profiles of children with ASD, with some children with ASD represented in each of the observed profiles.

Ultimately, since the BDI-2 continues to be widely used in the field, identifying distinct developmental profiles and their relationship, or lack thereof, to early ASD diagnosis could be leveraged to more quickly provide specialized care to children in EI.

The current study

In order to replicate findings from Elbaum et al. (2017), we conducted a confirmatory analysis to identify distinct developmental profiles based on the five domain scores of 57,966 children who completed a BDI-2 assessment and were enrolled in one of 12 Part C EI agencies in the state of Massachusetts. Notably, while 9.5% percent of children ages 0-3 in MA (the setting of this study) are enrolled in Part C EI services, only 2.3% of children ages 0-3 in Florida, where the prior study (Elbaum et al., 2017) was conducted, are enrolled in Part C EI services (Early Childhood Technical Assistance Center, 2019). Therefore, given potential significant differences between samples, it was considered that the findings from Elbaum et al., would not be generalizable to this sample. An analytic plan to attempt confirmatory LPA analyses as well as a plan to proceed in the event of model non-convergence was developed a priori.

Secondly, associations between class membership and sociodemographic factors (e.g., sex, race/ethnicity) were characterized. Subgroup analyses often fail to employ sufficient methodologies to estimate subgroup effects and rather rely solely on confirmatory or exploratory analyses (Varadhan et al., 2013). To avoid oversimplification and miscategorization of the heterogeneity of the data, subgroup analyses for this paper incorporated the expanded analytic framework outlined by Varadhan and colleagues (2013) and thus emphasized primarily descriptive analysis.

It is well documented in child developmental theories that environmental factors (e.g. socioeconomic status, parenting style) have a significant role in child development (e.g., Bronfenbrenner's ecological systems theory (1992)). Poverty, as it relates to child development, has been extensively researched. Evidence shows that while the duration and timing of poverty during a child's life may have differential impacts on subsequent development, children who have any experience of poverty on average show greater delays on measures of cognitive and socio-emotional development as compared to those who never experience poverty (NICHD Early Child Care Research, 2001, 2005). A recent study (De los Reyes-Aragon et al., 2016) however, found that while children ages 0 to 5 who were living in poverty in Colombia showed high rates of delay on the BDI-2 cognitive and communication domains, high rates of delay on the personal-social domain were not found. The authors conclude that factors such as socioeconomic status may have differential effects on BDI-2 domains. In this study we expected that health insurance status (public or private), which was used as a proxy for household income, would positively correlate with child developmental functioning as measured by the BDI-2, though likely not across all domains. More specifically, we hypothesized that having public insurance would predict a BDI-2 profile or class that demonstrates greater developmental deficits as measured by severity of BDI-2 scores and number of affected domains.

Disparities in rates of identification of developmental disabilities between males and females may be due to differing developmental phenotypes. One study conducted in Part C

EI compared the BDI-2 domain scores of 1,004 males and 313 females with ASD, as well as 6,465 males and 3,145 females without ASD (Matheis et al., 2019). For children with ASD, males showed greater delays in the communication domain while females showed greater delays in the motor domain. For children without ASD, males showed greater delays on the adaptive, communication, cognitive and personal-social domains than females did, while no sex difference was found for the motor domain. Another study (Messinger et al., 2013) comparing sex differences in developmental functioning using the Mullen Scales of Early Learning (Mullen, 1995) found in their sample, which included three-year-old children at low risk for ASD and those at high risk, that males demonstrated greater delays in both language and non-verbal domains than females. Overall, these findings indicate that males and females may score differently on domains related to developmental functioning, and that these differences vary by child diagnoses. For this study, we hypothesized that overall males would be more likely to belong to a class(es) that demonstrates greater deficits measured by severity of BDI-2 scores and number of affected domains as compared to females.

We also characterized the pattern of child age across latent classes based on developmental scores. We considered that children who enroll in EI services at an earlier age may be more likely to belong to classes that demonstrate greater developmental deficits as measured by severity on the BDI-2 and number of affected domains. Research shows a similar pattern for the identification of ASD; parents who reported that their child's ASD symptoms were severe received a diagnosis at an earlier age, on average, than those who reportedly had milder symptoms (Sheldrick et al., 2017). However, due to the rapid developmental changes that occur during this age period and differences in referral practices and enrollment reason (e.g., children who enroll in EI from birth because they have been classified as at-risk), younger children may in fact show less severe or no delays. Thus, we described the association between age and class membership.

Lastly, associations between class membership and race/ethnicity and primary language were described as we expected that there would not be equal representation of these demographic factors across classes.

For the third aim of this study, the association between ASD diagnosis and class membership is described. Given that the DSM-5 criteria for ASD require "persistent deficits in social communication and social interaction across multiple contexts," (pg. 50, APA 2013) we expected that children who meet criteria for ASD would belong to classes that show marked deficits in the communication and personal-social domains of the BDI-2. Further, results from previous research described above (Goldin et al., 2014) show that greater ASD symptom severity was associated with lower scores on all BDI-2 domains. Consistent with these findings, a recent study, using logistic regression, found that all five BDI-2 domain scores significantly predicted ASD screening outcome for children (N=13,781) in Part C EI (Peters & Matson, 2020). Taken together, we expected that ASD diagnosis would be associated with profiles that indicate greater challenges in developmental functioning.

Understanding developmental profiles of children in EI may be important for providing targeted, more individualized care and services for enrolled children. The goal of this study was to identify classes of children in Part C EI based on their developmental functioning measured by the BDI-2 through confirmatory latent profile analyses. We subsequently examined if a number of sociodemographic factors and ASD status predicted class membership.

Specific Aims

1. Replicate, using confirmatory analyses, the latent profile analysis conducted by Elbaum & Celimli-Aksoy (2017) to identify distinct classes based on child developmental profiles within our MA Department of Public Health (DPH) sample of 57,966 children. Given the large sample size, the sample was randomly split in two; a confirmatory LPA was conducted in the first half (N=28,983) and then replicated in the second half (N=28,983). Class indicators for the latent profile analysis were the five developmental domain scores (cognitive, communicative, adaptive, motor, personal-social) on the Battelle Developmental Inventory (BDI-2) collected at entry into EI.
2. Examine whether sociodemographic factors, including child age at entry into EI, child sex, child race/ethnicity, health insurance, and child primary language predict class membership (i.e., either replicated or newly derived classes). Child age, race/ethnicity and primary language are included as descriptive analyses.
3. Examine whether ASD diagnosis predicts class membership (i.e., either replicated or newly derived classes).

CHAPTER 2

RESEARCH DESIGN AND METHODS

Participants

Participants (N=57,966) were children enrolled in one of twelve Part C Early Intervention agencies in the state of Massachusetts from 2011 to 2019. Eligibility requirements for Part C EI Massachusetts are: a) child shows delays (1.5 standard deviations below the mean) in one of more areas of development, as indicated by a norm-referenced assessment (i.e. BDI-2), b) child has a medical condition that is associated with delay (e.g. genetic condition, vision loss), c) child is at risk for developmental delays due to a combination of multiple risk factors (e.g. low birth weight, feeding difficulties, trauma, parent chronic illness), or d) there is sufficient clinical concern regarding a child's development, as determined by a multidisciplinary clinical team (Massachusetts Center for Law and Education, 2012). The child must also be under three years of age to be enrolled in Part C EI. Children were eligible for this study if they completed the Battelle Developmental Inventory at EI entry and if their date of birth was documented in the dataset. Children in this study sample were primarily male (61.3%), represented diverse racial and ethnic backgrounds (see Table 1), primarily spoke English as their first language (74.5%) and were on average 15.46 months old at the time of evaluation. Nearly half of the sample (46%) was identified as publicly insured. Six percent of children in the sample had a record of an ASD diagnosis. For a full summary of demographic characteristics and eligibility reasons, see Table 1.

Procedures

Children in this study met eligibility criteria for EI and were enrolled in one of twelve MA Part C EI agencies between 2011 and 2019. During an initial appointment at an EI agency to determine eligibility for early intervention services, each child was evaluated to determine his/her level of developmental functioning using the Battelle Developmental Inventory, Second Edition (BDI-2; Newborg, 2005). The BDI-2 was conducted by one or more providers, as per the instrument's administration protocol. BDI-2 data, demographic data, and ASD diagnosis data were collected by the EI agencies and collated by the Massachusetts Department of Public Health (DPH).

This study has been approved by the Massachusetts DPH institutional review board (IRB) and by the research team's University IRB.

Measures

Demographics. Information about the child and family for all children in the overall sample was obtained using a dataset provided by the MA DPH, that was comprised of EI agency administrative records. Variables of interest for this study were: child age, child sex, child race/ethnicity, child primary language, health insurance status.

Developmental functioning. The Battelle Developmental Inventory (Newborg, 2005; Newborg et al., 1984) is a norm-referenced assessment used to measure developmental status for children between the ages of 0 and 7 years and 11 months. Revisions in the second edition of the Battelle Developmental Inventory (BDI-2; Newborg, 2005) decreased the number of subdomains, added new materials to facilitate child engagement (workbook, visual stimuli), expanded the normative sample and tables with smaller corresponding age ranges, and added new rules to control for floor and ceiling effects (Bliss, 2007). The standardization sample included 2,500 children who closely resembled census data from the year 2000 for child sex, ethnicity, education and religion. Children who were classified as having "acute medical conditions, marked sensory or communication deficits, or severe behavioral or emotional disturbances" (pg. 26, Alfonso et al., 2010) were excluded from the normative sample. Materials for BDI-2 administration are available in Spanish, though it has not been normed for Spanish-speaking populations (Cunha et al., 2018).

There are five domains of the BDI-2—communication, cognitive, motor, adaptive and personal/social. Scores pertaining to domain are reported as developmental quotients (DQs) which are standard scores. Domain DQs and the total DQ, which is used to summarize a child's overall developmental functioning, range from values of 55 to 145 (M=100, SD=15). Lower scores indicate greater delays. As previously mentioned, the psychometric properties of the BDI-2, reported in the administration manual, are strong.

The BDI-2 can be administered by most professionals (e.g., schoolteacher, EI provider) and further, different professionals can administer individual domains of the assessment (a speech and language pathologist conducts items related to the communication domain, an occupational therapist conducts items related to the adaptive domain). The administration method of the BDI-2 is flexible, largely dependent on the needs of the child and the skill that is being assessed. Items can be completed through structured activities, observations, or parent interviews; all method options for each item are listed in the manual. Scoring processes are straightforward and outlined in the administration manual; raw scores are converted into scaled scores, age equivalents and percentile ranks. In this study, the BDI-2 was administered by the child's EI provider(s), as per the protocol for EI eligibility in the state of Massachusetts.

ASD Diagnosis. Presence of ASD diagnosis was coded from DPH data files. Presence of ASD was coded if a child was recorded as having ASD at enrollment, if a new diagnosis of ASD was indicated during the time of EI enrollment, and/or if the child received ASD-specific services during the time in which they were enrolled in EI.

Data Analysis Overview

Data was analyzed using two statistical packages: Stata 16.0 and Mplus (Muthén & Muthén, 2017). Prior to testing the specific aims, descriptive statistics (mean, standard deviation, skewness, kurtosis, etc.) for BDI-2 domain scores, demographics and ASD diagnostic data were obtained using Stata. Rates and patterns of missingness were explored for key variables.

Statistical Analyses for Specific Aim 1. Latent profile analysis (LPA) is used to sort "individuals from a heterogenous population into smaller, more homogenous subgroups based on individuals' values on continuous variables." (pg. 182, Berlin, Williams, & Parra, 2014). In an attempt to replicate findings from the only known previous study (Elbaum & Celimli-Aksoy, 2017) that identifies latent classes of children in Part C EI based on their developmental profiles, a confirmatory LPA analysis was conducted in Mplus (Muthén & Muthén, 2017). For this study and that done by Elbaum and colleagues the continuous variables, or latent class indicators, were the five domain-level developmental quotients (DQs)—Adaptive, Communication, Cognitive, Motor, Personal-social.

Prior to conducting LPA analyses, the full sample (N=57,966) was randomly split in half yielding two samples equal in size; the confirmatory LPA was conducted with sample 1 and then replicated with sample 2. Upon replication, the samples were combined again and identical CLPA analyses, as described below, were conducted for a third time with the full sample.

For the confirmatory analyses, first a 4-class solution was tested using start values from Elbaum et al.'s study. The only fixed parameters were the mean and variance of the communication domain for one class, which were fixed at 55 and 0.500 respectively. Class enumeration for three-, five-, six-, and seven-class models followed with the same start values and fixed parameters for the first 4 (or 3) classes. Homogeneity of covariance within class was required, as it was in the original study. Models used the maximum likelihood estimation method (Masyn, 2013). The number of random starts, which is useful to determine convergence on a model (Nylund-Gibson & Choi, 2018), was increased from that of Elbaum et al. due to our larger sample size. Model convergence was determined by a comparison of the several fit indices, as is recommended for LPA analyses (Berlin et al., 2014), including log likelihood estimates, Bayesian information criterion, sample-size adjusted Bayesian information criterions, and consistent Akaike information criterion. Lower values of information criteria indices indicate better fit of the model. Additionally, entropy and the Lo-Mendell-Rubin, a likelihood ratio test, were included to further evaluate each model's fit. Entropy scores (range 0-1) convey how likely a model is to classify an individual into a single class; scores closer to 1 demonstrate better accuracy of the model (Berlin et al., 2014; Williams & Kibowski, 2016). Likelihood Ratio Tests provide p-values which indicate if adding one more profile to the model is a significant improvement. Though the information from these tests and indices were not in full agreement with one another, as is common in mixture modeling, all of the information was used together to determine which model best demonstrates the true latent patterns in the data. Latent classes were subsequently named by considering relative profile shape, ease of interpretability and in consultation with an expert panel.

Statistical Analyses for Specific Aim 2. To determine if sociodemographic (age, sex, race/ethnicity, primary language, health insurance status) factors predict class membership (Aim 2), we conducted a multinomial regression in Mplus using Vermunt's three-step (2010) approach which properly accounts for classification error. Child age was the only continuous predictor. For the purposes of regression analyses, child primary language was recoded into a binary variable (English and Other) and so too was child race/ethnicity (White, non-Hispanic and child of Color or White, Hispanic). Regression analyses were conducted with the full sample (N=57,966). Vermunt's approach (2010) does not classify and assign individuals into a class but uses modal probabilities to achieve the lowest rate of classification error. By separating estimated assigned class probabilities from true class probabilities and eliminating the assigned class variability, classification error is reduced (Nylund-Gibson & Choi, 2018; Vermunt, 2010).

Statistical Analyses for Specific Aim 3. Similar to analyses conducted for sociodemographic factors, to determine if ASD diagnosis was associated with latent class membership (Aim 3) we conducted a multinomial regression in Mplus (N=57,966) using Vermunt's three-step (2010) approach.

CHAPTER 3

RESULTS

Preliminary Statistical Analyses

Table 1 provides a description of demographics and ASD diagnosis data for the full sample, including rates of missingness (N=57,966). Demographic variables were missing relatively little data with the exception of health insurance. Domain DQ means and rates of missingness are provided in Table 2. Rates of missingness were exceptionally low for BDI-2 domain DQs. Additionally, domain DQ scores were relatively normally distributed as indicated by measures of skewness and kurtosis. Intercorrelations for domain DQs are provided in Table 3. Overall, domain DQs were moderately positively correlated with one another (range 0.27-0.44) with the exception of Communication and Motor which reflected a very weak correlation and Cognitive and Personal/Social which reflected a large correlation.

Confirmatory LPA: Split Samples

Results for the confirmatory LPA analyses in sample 1 were replicated in sample 2, as determined by an empirical evaluation of the configural, structural, dispersion and distributional similarities (Morin et al, 2016) between the samples. Thus, this paper presents CLPA findings for the full sample.

Confirmatory LPA: Full sample

Class enumeration for the full sample was conducted for three- four- five- six and seven-class models. Model fit statistics are provided in Table 4. The log likelihood (LL), Bayesian Information Criteria (BIC), Akaike Information Criterion (AIC), sample size adjusted BIC (ssBIC) and consistent Akaike information criterion (CAIC) are lower for class three than class two and lower for class four than class three. The fit indices are only marginally smaller for classes five, six and seven as compared to the four-class solution. The numeric values of the fit indices for each model were plotted to facilitate in interpretation (Nylund-Gibson & Choi, 2018); see Figure 1. The four-class model marks the elbow or plateau of the curve, which in LPA methods typically indicates the most optimal, parsimonious fit (cite). The Lo-Mendell Rubin (LMR) likelihood ratio test indicates that the 3-class solution fits better than the 2-class solution, the 4-class solution fits better than the 3-class solution and that the 5-class solution fits better than the 4-class solution. LMR tests for 6-class and 7-class models could not be computed, which can occur in some complex models; in such instances the BIC can be used instead (Nylund, Asparouhov, Muthen, 2007). Entropy is largest for the two-class model (0.92) followed by the class four model (0.78) indicating better accuracy of classification than the other models. Given evaluation and interpretation of the fit indices above, as well as consideration of previous findings (Elbaum et al., 2017), we concluded that a 4-class solution provided the best fit. The classification probabilities (i.e., most likely latent class membership) for the 4-class solution were relatively large and ranged from 0.84-0.97 (See Table 5).

Developmental profiles for the four-class solution

Table 6 provides the five domain means and standard deviations, and relative class size for each of the four classes. Classes were variable in size; for example, Class 4 described 49.7% of the sample whereas Class 3 described 7% of the sample. Figure 2 visually depicts the within-profile means by each of the 4 classes. To better understand the heterogeneity within class, random sample (N=15) plots were created for each profile and are provided in Appendix A.

The four classes were labeled in order to highlight the relative delays and strengths for each profile, keeping in mind that a DQ below 70 indicates 2 standard deviations below the Battelle's mean (M=100, SD = 15). Overall, Class 1 was characterized by a relatively low communication DQ (below 70) and high motor DQ, with the other DQs falling relatively level in the between communication and motor. Class 2 showed a pattern that was qualitatively similar to Class 1 though all of the DQs were higher, indicating milder delays (communication still fell below 70). We therefore labeled Class 1 "Marked communication delay, relative motor strength" and Class 2 "Communication delay, average motor functioning." Class 3 showed a pattern of more severe delays in cognitive and motor DQs relative to other classes and relative to other DQs within-class, and relatively higher functioning in the adaptive domain compared to other DQs within-class. Thus, we labeled Class 3 "Cognitive and motor delays, relative adaptive strength." Overall, Class 4 showed higher DQs across all domains relative to the other classes. We labeled Class 4 "Consistent mild delays."

The pattern of profiles both within and between the four classes is remarkably similar patterns to that of the previous study (Elbaum et al., 2017). A visual comparison of the current study's four-class solution and that found in the original study (Elbaum et al., 2017) is provided in Figure 3.

Predictors by class membership: Frequencies

Frequencies of child characteristics (i.e., predictors) within each of the four classes are presented in Table 7. For example, it is estimated that 27% of children in the Marked communication delay, relative motor strength class are female whereas 44% of children in the Consistent mild delay class are female. In regard to ASD diagnosis, it is estimated that 22% of children in the Marked communication delay, relative motor strength received an ASD diagnosis, whereas 3% of children both in the Cognitive and motor delays, relative adaptive strength class and the Consistent mild delays class received an ASD diagnosis. Of note, these frequencies were determined using the classify-and-assign approach to class membership, and thus these percentages are only estimates because they do not take into account classification error.

Predictors by class membership: Multinomial logistic regression

The total number of cases included in the regression model was 56,958. Class 4 was the largest and therefore the reference class to which all of the other classes were compared. The output of the regression model is displayed in Table 8. Odds ratios are also provided in Table 8 and indicate change in the likelihood that an outcome will occur, in this case membership in one class versus another, given one unit of increase in the predictor variable. Overall, predictors had significant implications for profile membership.

Since Full Information Maximum Likelihood (FIML) is not possible for auxiliary variables in multinomial regression analyses in Mplus, and the insurance variable had a significant number (~12,000) of missing values, this predictor variable was excluded from the primary model shown in Table 8. A regression model that includes insurance is presented in Appendix B; insurance was only significant for one class comparison (Class 2 vs Class 4).

Marked communication delay, relative motor strength (Class 1) vs. Consistent mild delays (Class 4). As shown in Table 8, for this class comparison, all coefficients were significant at the $p<.01$ level. Older children, males, children of color, children who spoke a primary language other than English and children diagnosed with ASD were significantly more likely to belong in Class 1 relative to Class 4 (purple/reference class).

For this class comparison, the odds ratio for ASD diagnosis was the largest, indicating that members of Class 1 were 9.7 times as likely to have an ASD diagnosis relative to members of Class 4. The odds ratio for age was also large; members of Class 1 were 7.2 times as likely to be a year older relative to members of Class 4. All other odds ratios were statistically significant yet indicated a much smaller effect of the predictor on class membership.

Communication delay, average motor functioning (Class 2) vs. Consistent mild delays (Class 4). For this class comparison, all coefficients were significant at the $p<.01$ level. Older children, males, children of color, children who spoke a primary language other than English and children diagnosed with ASD were significantly more likely to belong in Class 2 relative to Class 4.

Odds ratios for all predictors were significant and reflected that predictors had a mild effect on class membership with the exception of child age which reflected a large effect. Members of Class 2 were 5.3 times as likely to be a year older relative to members of Class 4.

Cognitive and motor delays, relative adaptive strength (Class 3) vs. Consistent mild delays (Class 4). Younger children, children of Color and children who spoke a primary language other than English were significantly more likely to belong in Class 3 relative to Class 4. Males and those with an ASD diagnosis were marginally significantly more likely to be in Class 3 relative to Class 4.

All odds ratios were statistically significant. Classes significantly differed with respect to sex, race, primary language spoken and ASD diagnosis. The largest odds ratio found was age; children in Class 3 were markedly more likely to be younger relative to children in Class 4.

CHAPTER 4

DISCUSSION

Using confirmatory latent profile analysis, this study of a large population of infants and toddlers enrolled in the Part C Early Intervention System replicated previous findings (Elbaum et al., 2017). Consistent with Elbaum and colleagues, we found four latent developmental profiles of children entering Part C EI. The four profiles were labeled "Marked communication delay, relative motor strength" (Class 1); "Communication delay, and average motor functioning" (Class 2); "Cognitive and motor delays, relative adaptive strength" (Class 3); "Consistent mild delays" (Class 4). The model had good classification probabilities, (i.e., >0.70; Nagin, 2005, Nylund et al 2018) and adequate entropy indicating statistical support for the acceptability of the four-class solution. The "Marked communication delay, relative motor strength" class demonstrated particularly strong classification probabilities indicating that children who were modally assigned to this class had a 3% chance of belonging in any other class. While entropy was just under 0.80, it matched that of Elbaum et al.'s (2017), suggesting comparable accuracy of the four-class model across studies.

Elbaum and colleagues (2017) previously described the association of age and ASD status with class membership. As an extension of their findings, our study also examined the association of sociodemographic factors (sex, race, primary language spoken, and insurance) with class membership, in addition to ASD status and age. Findings show that the four classes differed in group composition in relation to demographic factors. The effects of age and ASD status were particularly large in the prediction of class membership. Overall, children who were younger generally demonstrated a profile consistent with the "Cognitive and motor delays, relative adaptive strength" class. Children who had a record of an ASD diagnosis were most likely to demonstrate a profile consistent with the "Marked communication delay, relative motor strength" class.

Comparison of current study's profiles and those of original study (Elbaum et al., 2017).

The pattern (i.e., means) within and between the four profiles for the current study were remarkably similar to that of the previous study (Elbaum et al., 2017), further supporting the replication. We found two parallel profiles categorized by relatively low communication capabilities, relative to other domains, as did Elbaum et al. (2017). The other two profiles demonstrated relatively level functioning across domains and were differentiated by severity of delays (i.e., one profile demonstrated greater delays and one demonstrated lesser delays across domains). A similar pattern was reported by Elbaum et al. (2017), although for Class 3 (which we labeled "Cognitive and motor delays, relative adaptive strength") they found relatively level and low functioning across cognitive, communication and motor domains whereas in this study communication was relatively higher. Nonetheless, their primary conclusion, that there are two broad profiles of developmental functioning among children in EI— those that exhibit a primary and relative deficit in communication and those that exhibit more consistent deficits or delays across domains—was replicated in the current study.

Notably, the profile DQ means for the current study were generally the same or higher than those found previously by Elbaum et al. (2017) (see Figure 3). In particular motor DQs in this study were most consistently higher than those previously reported across all profiles. These discrepancies may be due to differing EI eligibility criteria between states. Massachusetts has relatively less stringent eligibility criteria (Massachusetts Center for Law and Education, 2012) than Florida (Agency for Health Care Administration, 2007) and therefore enrolls a greater percent of the population aged zero to three years (Early Childhood Technical Assistance Center, 2019). Our results suggest that even when the eligibility criteria for EI entry are changed, the structure of the latent classes remains stable; while the DQs are higher, the profile patterns remain quite similar. It would be reasonable to expect that less stringent eligibility criteria would create an additional class or subgroup of children in EI with less severe delays across domains. Our findings suggest, however, that children within the same profiles are being captured when eligibility criteria are relaxed, even if overall some of the children demonstrate less severe delays.

Relative class size, or the proportion of the total sample belonging to each subgroup, was also consistent across the original and current study for Classes 1 and 3. Approximately thirteen percent of our sample comprised the “Marked communication delay, relative motor strength” class whereas 15.5% of Elbaum et al.’s (2017) sample was assigned to the class we label “Marked communication delay, relative motor strength.” Seven percent of the current study’s sample comprised the “Cognitive and motor delays, relative adaptive strength” class; the same was true for Elbaum et al.’s (2017) corresponding class. Interestingly, in the current study the “Communication delay, average motor functioning” class contained approximately 30% of the sample and the “Consistent mild delays” class contained approximately 50% of the sample. The reverse was reported by Elbaum et al. (2017). In their study, 47% of their sample was assigned to the class we label “Communication delay, average motor functioning” class whereas 30% of their sample was assigned to the class we label “Consistent mild delays.” Given that the “Consistent mild delays” class in this study represents the subgroup with the least significant developmental delays across domains, it may be that this class is relatively larger in our findings, compared to that in Elbaum et al. (2017), given the more inclusive criteria for MA EI relative to FL EI system.

Demographic differences between profiles

Results showed that profiles significantly differed on nearly all demographic factors examined (see Table 8), and this was particularly true for ASD status and age. While Elbaum et al. (2017) did not examine child sex, race, primary language spoken, or insurance status, our findings are relatively consistent with their findings for age and ASD status.

Age. Consistent with Elbaum et al.’s (2017) findings, we found that older children were more likely to belong to one of the two communication delay, and motor strength classes compared to the “Consistent mild delays” class (i.e., reference class). Communication delays are identified more frequently in toddlerhood rather than infancy, with the majority of research on identification of language delays in young children focusing on the 24-30 month age range (Dale & Patterson, 2017). This likely contributes to the increased age of both classes that are characterized by communication delays. In contrast, given the very young average age of the "Cognitive and motor delays, relative adaptive strength" class, it is likely that these children were eligible for EI at birth. A possible interpretation of these findings suggests that there are subgroups of children that demonstrate increased differentiation in patterns of developmental functioning as they age. This study was based on EI evaluation data and thus it was cross-sectional and assessed children at different points on their developmental trajectories. Therefore, classes may reflect inter- or intra-person differences. For example, relative weaknesses in communication may emerge or be identified as expectations related to the sophistication of age-expected communication skills grow. Taken together, our findings and previous research suggest that child age may impact developmental profile over time.

Sex. Males were disproportionately represented in both "Communication delay, and relative motor strength" classes compared to the "Consistent mild delays" class. Though the effect was quite small, males were also more likely to have a profile consistent with the "Cognitive and motor delays, relative adaptive strength" class as compared to the "Consistent mild delays" class. These findings align with our hypotheses and previous evidence suggesting that males exhibit greater delays, especially communication delays, on measures of developmental functioning relative to females (Matheis & Matson, 2015; Messinger et al., 2013). These findings however contradict recent findings from a study (Wiggins et al., 2021) evaluating sex differences in developmental functioning among preschool-aged children, using the Mullen and Child Behavior Checklist. Study results indicated that neither for children with an ASD diagnosis (N=1,480) nor for those with subclinical ASD characteristics (N=593) were there sex differences in developmental functioning. Our results, in light of these findings, may indicate that the Battelle does produce sex effects differently from other measures of developmental functioning. Alternatively, our results may indicate differential patterns in developmental functioning by sex rather than individual domain differences.

In regard to sex and ASD diagnosis, both Communication delay, and relative motor strength classes, which had disproportionate representation of males, were also most likely to represent children with ASD. This aligns with previous research documenting sex differences in developmental functioning for young children with ASD (e.g. Carter et al., 2007). At the same time, some evidence suggests that measures of developmental functioning and criteria for ASD diagnosis are biased towards identification in males rather than in females (Haney, 2016). It is possible in this study that the sex differences found are influenced by the biases in the measure. Of note, while the standardization sample matched the US population make-up in terms of sex (Alfonso et al., 2010; Bliss, 2007) the validity of the Battelle Developmental Inventory—Second Edition for males and females is has not been independently studied.

Race and primary language. Overall, children of Color and children who spoke a primary language other than English were more likely to demonstrate a profile consistent with one of the three classes indicative of moderate to severe deficits. Though the odds ratios indicated mild associations, these findings are consistent with literature (e.g., Jarquin et al., 2011; Tek & Landa, 2012) that suggests children with marginalized identities often receive developmental diagnoses and services only when more severe delays and symptoms are present. Therefore, our findings likely reflect lack of access to EI services and systemic barriers to EI entry for children from minoritized backgrounds who have less severe delays.

A second important consideration in the interpretation of these findings is related to the use of the Battelle with diverse populations. A test review (Bliss, 2007) of the Battelle Examiner's Manual indicates that "if a child is a recent immigrant or unfamiliar with the predominant culture, examiners should be cautious in interpreting BDI-2 results" (pg. 410); it is likely that "predominant culture" refers to the US White English-speaking middle-class culture in which the measure was normed. Thus, our findings may represent a function of the test characteristics in a multicultural, multilingual sample. Alternatively, given that developmental risk factors are often experienced by children and families with marginalized identities, results may accurately represent child developmental functioning.

Lastly, that the "Consistent mild delays" class (i.e., the reference class) included relatively more White children and children who spoke English as their first language relative to the other classes, and that this class was larger than the previous study (Elbaum et al., 2017), brings into question how more inclusive eligibility criteria impacts the demographic make-up of children in Part C EI. A possible interpretation suggests disparities in access to EI, because of social determinants of health and systemic barriers, that result in White children with mild delays entering the EI system at higher rates than children of Color with mild delays.

Insurance. Despite our hypothesis that socioeconomic status would be associated with class membership as well as previous literature documenting the association between socioeconomic status (SES) and child developmental functioning (e.g., De los Reyes-Aragon et al., 2016; Hackman & Farah, 2009) insurance status, our proxy for socioeconomic status, did not predict class membership at the $p<.01$ level for any of the class comparisons (See Appendix B). Odds ratios ranged from 0.916-1.054. Insurance status may have been insufficient in capturing SES, especially since many children who qualify for EI also qualify for public insurance, and may contribute to our lack of significant findings.

ASD. The four profiles differed in regard to ASD status. As hypothesized, given known associations between communication delays, and ASD characteristics and diagnostic criteria (DSM-V), children on the spectrum were most likely to have a profile consistent with the “Marked communication delay, relative motor strength” class, which demonstrated the greatest deficit in communication. This effect was large. Children with ASD were also more likely to have a profile consistent with the “Communication delay, average motor functioning” class as compared to the reference class. These findings are consistent with that of Elbaum et al. (2017).

Interestingly, recent evidence suggests that motor delays in early childhood may be an early indicator of ASD (Harris, 2017) and that for toddlers (12-36 months of age) with ASD, motor delays increase over time (Lloyd et al., 2013). In our sample however, the two profiles (“Marked communication delay, relative motor strength” and “Communication delay, average motor functioning” classes) which represented the majority of children with ASD showed overall relative motors strengths. While these findings appear to contradict previous research, it may be, given that approximately only 22% and 5% of children belonging to these profiles had an ASD diagnosis, that the relative motor strength characteristic of these profiles is not consistently exhibited on an individual level by children on the spectrum.

Despite the fact that the majority (estimated 50%) of children with ASD in our sample had a profile consistent with the “Marked communication delay, relative motor strength” class, approximately 24% had a profile consistent with the “Communication delay, average motor functioning” class, and 23% with the “Consistent mild delays” class. One explanation for this, given previous findings which suggest ASD symptom severity impacts overall DQ (Goldin et al., 2014), is that children on the spectrum had profiles consistent with certain subgroups based on their autism symptom severity. For example, children with less severe autism symptom severity may belong to the “Consistent mild delays” class whereas those with greater symptom severity may belong to the “Marked communication delay, relative motor strength” class. It is likely that children on the spectrum who belong to different subgroups will need different interventions to optimize their developmental outcomes. Though our results identify, on a population level, profiles that demonstrate higher risk for ASD, individual children show marked heterogeneity on the Battelle within each developmental profile class; thus, our findings contraindicate a uniform approach to ASD intervention and treatment.

While Elbaum et al. (2017) found that approximately 5.4% of children on the spectrum belonged to the class that corresponds with our “Consistent mild delays” class, in our study 23% of these children were estimated to show a profile consistent with this class. This discrepancy may again be due to differing eligibility EI criteria between samples, as well as our larger sample size.

Lastly, the likelihood of children on the spectrum having a profile consistent with "Cognitive and motor delays, relative adaptive strength" was very low. This is unsurprising given the low mean age of children in this class, the typical time window of ASD diagnosis and evidence which suggests that behavioral signs of ASD do not manifest until approximately 12 months of age (Ozonoff et al., 2010). Further, it is possible ASD diagnosis data for children in this class in particular, given their young age, was not collected during their window of risk (i.e., 18-36 months of age) due to external factors (e.g., discontinuing EI services, moved away, timing of data pull). Therefore, the true proportion of children on the spectrum in this class is unknown and is likely under-represented in this dataset.

Person-centered analyses and heterogeneity in EI

Latent profile analysis aims to find similar groups, or relative homogeneity, within a heterogenous population. The person-oriented approach of latent profile analysis allows a better understanding of common relative strengths and challenges among children in EI. Results of such analyses may help EI providers better understand the treatment needs or risk factors for the children they serve. At the same time, in a national study of Part C EI, Scarborough et al., (2004) conclude that "there is no such thing as a typical child in early intervention" (480). While this was primarily reported in reference to eligibility reason, as well as children and family characteristics (e.g., income, education), their conclusion is relevant to our study findings. Random sample plots of 15 children in each class (see Appendix A) visually demonstrate the variation within classes. Thus, a comprehensive interpretation of study findings includes an emphasis on the fact that the four profiles do not explain all of the heterogeneity in developmental functioning for children in EI.

Limitations and Future Directions

Despite this study's very large diverse sample, use of person-oriented approach and the successful replication and extension of an earlier study, there were a number of limitations. First, the study was cross-sectional and it is not known if profile membership is static. While we found that age was associated with class membership, it may be that there are age effects which impact child profile and subgroup membership. While results indicate demographic differences between subgroups, it may the four class solution may not work equally well for all children (e.g., girls vs. boys, children of Color vs. White non-Hispanic children). For example, if the sample was restricted to girls only would a four-class solution with similar profile structure represent the data well? Given these stated limitations, further research in this area is needed to determine if profiles are consistent across time and among various demographic groups. Further, in this study only Battelle domain scores were used in the examination of developmental profiles of children in EI. The inclusion of more nuanced information such as autism symptomatology and social-emotional and behavioral competencies would be beneficial in future studies. Lastly, the children in this study were enrolled in one of 12 EI agencies throughout the state of MA, however they may not be representative of all children in EI nationwide.

Given that the mean age of diagnosis in the US is over age three years (Baio et al., 2018), children in our study who are categorized as not having an ASD diagnosis may be miscategorized, and this may be especially true for the youngest children in our sample. Thus, the generalizability of our findings is limited, specifically in regard to ASD prevalence within the sample and within subgroups. Black and Hispanic children, poor children and children whose primary language is one other than English are systematically under identified with ASD (Arunyanart et al., 2012; Guthrie et al., 2019; Zuckerman et al., 2017); this is one reason why there may be more children on the spectrum in our sample than we indicate, which could ultimately change the prevalence of ASD across subgroups. Relatedly, our data for ASD diagnosis only captures those who remained in EI through the window of ASD risk. Children in this study who left EI before 18-30 months may in fact be on the spectrum but this information is unavailable. The sample for this study could have been restricted to children who stayed in EI until at least 30 months however this would have resulted in a loss of power.

Lastly, conclusions drawn from Battelle Developmental Inventory data are inherently limited. It is unknown how much data was parent-reported versus how much was observed child behavior, and if this changed depending on the age or developmental functioning of the child. Additionally given that the Battelle is in part an observation- and in part a parent-interview-based measure, results may be influenced by interviewer or coder implicit biases related to race, ethnicity and language (Zuckerman et al., 2014) or differences in cultural meanings attributed to parent-interview-based items. There are known limitations of current child development assessment practices which include the fact that developmental norms and diagnostic criteria have largely been established based on White European English-speaking children (Espinosa, 2015; Norbury & Sparks, 2013). Though standardization for the Battelle Developmental Inventory—Second Edition (Newborg, 2005) included a sample that aligned with U.S. Census data in the early 2000s (Alfonso et al., 2010; Bliss, 2007), the psychometrics of the Battelle are understudied (Cunha et al., 2018). It is likely that there are racial, cultural and language biases in the evaluation using the Battelle which affect the validity and generalizability of the measure and our findings. Given the continued widespread community use of the Battelle in EI settings, research on its reliability and validity among diverse populations is critical.

Finally, greater understanding about how profile membership interacts with EI effectiveness and treatment outcomes in the short and long term would be clinically useful, as it could indicate for whom is EI working. Elbaum et al. (2017) explored how profiles related to developmental trajectories in their sample and further investigation is warranted. Evidence suggests that earlier treatment and service receipt are associated with better child developmental outcomes (e.g. Remington et al., 2007; Zwaigenbaum et al., 2015). If it is found that EI currently works better for a certain profile over another, this could highlight opportunities for targeted treatment to children with specific developmental profiles starting at EI entry.

Clinical Implications

The identification of common Battelle profiles for children in EI can help EI providers tailor interventions to meet child needs in a systematic manner. Our findings illustrate that children in EI have a variety of strengths and challenges in regard to developmental functioning, and this certainly negates a standard or uniform treatment for all children in EI. Findings also suggest that Battelle developmental functioning profiles provide information about child risk and treatment for autism. Given diagnostic odds ratios between 5 and 9, the positive predictive values of class membership with respect to ASD are meaningful but also not diagnostic. Clinical decisions should never be made based only on one data point, such as a child's Battelle profile, however our findings suggest profile does provide another piece of information in the consideration of ASD risk. Finally, while developmental profiles do provide useful information for the conceptualization of child functioning, comprehensive care in EI continues to include evaluations of symptom severity, caregiver-child relationships, social/emotional functioning and the context of the child's broader community.

Conclusions

The replication crisis within the field of psychology has been well documented (Open Science Collaboration, 2015); this study serves as a welcome counterexample to this phenomenon. The current study, using a large sample (N=57,966) replicated findings from a smaller study (N=1,513; Elbaum et al., 2017) investigating the developmental profiles of children in Part C EI. The identification of latent profiles of child developmental functioning provides an opportunity to make sense of some of the heterogeneity of children in EI. Results suggest that 1) Battelle developmental profiles may be an additional indicator to improve identification of ASD risk in community settings and 2) child developmental profile could guide streamlined but person-oriented service receipt by tailoring interventions to specific child developmental needs. Continued research is necessary to determine if profile membership is consistent across time.

Table 1

Demographics of full sample (N=57,966)

Demographic Variables		
	M	**SD**
Child age (in months) at EI entry	15.46	9.93
	n	**%**
Child sex		
Female	22,437	38.71
Male	35,529	61.29
Child race/ethnicity		
Asian/Pacific Islander, non-Hispanic	4,375	7.55
American Indian/Alaska Native, non-Hispanic	108	0.19
Black, non-Hispanic	6,224	10.74
Hispanic, Black	1,386	2.39
Hispanic, multiracial/ethnic	2,431	4.19
Hispanic, White/unspecified	14,777	25.49
Multiracial/multiethnic	2,019	3.48
White, non-Hispanic	26,318	45.40
Other	3	0.01
Unknown/missing	325	0.56
Child primary language		
English	43,171	74.48
Spanish	8,497	14.66
Other	5,583	9.63
Unknown/missing	715	1.23
Record of ASD diagnosis?		
Yes	3,526	6.08
No	54,440	93.92
Insurance Status		
Public	26,868	46.35%
Private	18,788	32.41%
Unknown/missing	12,310	21.24%
Eligibility reason		
Established condition(s)	1,332	2.3
Established delay(s)	42,347	73.06
At risk condition(s)	1,816	3.13
Est. condition & Est. delay	2,761	4.76
Est. condition & at risk condition	152	0.26
Est. delay & at risk condition	5,992	10.34
Est. condition, est. delay & at risk condition	910	1.57
Clinical judgement	2,656	4.58

Note. Missingness was 0% for child sex, ASD diagnosis, and eligibility reason.

Table 2

Descriptive statistics for the five Battelle Developmental Inventory domain developmental quotients (DQs)

Domain DQ	**n**	**nMiss**	**M**	**SD**	**Median**	**Skewness**	**Kurtosis**
Adaptive	57,906	60	84.17	13.56	85	0.11	3.04
Cognitive	57,930	36	80.34	13.14	80	0.19	2.69
Communication	57,936	30	71.24	13.06	70	0.75	3.29
Motor	57,923	43	89.06	16.50	92	0.20	2.11
Personal/Social	57,942	24	82.16	11.09	82	0.15	3.15

Table 3

Intercorrelations of domain DQs

Domain DQ	**Adaptive**	**Cognitive**	**Communication**	**Motor**	**Personal/Social**
Adaptive	1				
Cognitive	0.3017	1			
Communication	0.3014	0.3012	1		
Motor	0.2738	0.4236	0.0866	1	
Personal/Social	0.4333	0.5625	0.4355	0.3532	1

Table 4

Model fit statistics from class enumeration

					Parsimony Criteria				
Classes	**N**	**parms**	**LL**	**Entropy**	**AIC**	**BIC**	**CAIC**	**ssBIC**	**LMR**
2	57966	39	-1118961.94	0.92	2238001.89	2238351.62	2238390.62	2238227.68	p<.001
3	57966	60	-1113232.64	0.76	2226585.27	2227123.33	2227183.33	2226932.65	p<.001
4	57966	81	-1108485.26	0.78	2217132.51	2217858.89	2217939.89	2217601.47	p<.001
5	57966	102	-1106654.57	0.74	2213513.15	2214427.84	2214529.84	2214103.68	p<.001
6	57966	123	-1106214.19	0.73	2212674.37	2213777.39	2213900.39	2213386.49	--
7	57966	144	-1104277.94	0.71	2208843.87	2210135.21	2210279.21	2209677.57	--

Parms = number of parameters; LL = loglikelihood; AIC = Akaike Information Criterion; BIC = Bayesian Information Criteria; CAIC = Consistent Akaike Information Criterion; ssBIC = sample size adjusted Bayesian Information Criteria; LMR = Lo-Mendell Rubin

Table 5

Classification probabilities for the most likely latent class membership (column) by latent class (row) for the four-class solution

Class	**1**	**2**	**3**	**4**
1	0.968	0.020	0.002	0.011
2	0.036	0.844	0.000	0.120
3	0.028	0.001	0.920	0.051
4	0.008	0.111	0.017	0.864

Table 6

Domain DQ means and relative size for four-class solution

Class	Communication		Cognitive		Motor		Adaptive		Personal Social		Relative Class Size
	Mean	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Proportions**
1	55.00	0.71	71.29	11.24	85.41	15.18	74.08	12.48	70.85	9.81	0.128
2	64.53	5.91	83.21	10.78	98.99	10.10	85.89	12.69	84.16	10.50	0.305
3	71.58	9.11	60.31	1.84	65.20	5.70	79.73	11.35	73.13	7.23	0.070
4	79.46	12.15	83.59	12.50	87.28	16.59	86.33	13.32	85.03	9.78	0.497

Table 7

Estimated distribution of predictor variables within classes

Covariates		Class 1 (Orange)	Class 2 (Green)	Class 3 (Light Blue)	Class 4 (Purple)
Age, M(SD)	In years	1.86(0.45)	1.67(0.57)	0.27(0.41)	1.02(0.85)
Sex	Female	27%	35%	45%	44%
	Male	73%	65%	55%	56%
Race	Child of Color	65%	58%	54%	49%
	White, non-Hispanic	35%	42%	46%	51%
Insurance	Private	38%	42%	34%	43%
	Public	62%	58%	66%	57%
Primary language	English	67%	71%	79%	80%
	Spanish or other	33%	29%	21%	20%
ASD diagnosis (dx)	No dx	78%	95%	97%	97%
	Yes dx	22%	5%	3%	3%

Note: Insurance has ~12,000 missing cases and was removed from the final regression model but is listed here for descriptive purposes.

Table 8

Multinomial logistic regression evaluating effect of predictors on latent profile membership.

	Marked com. delay, relative motor strength (1) vs. Consistent mild delays(4)			Com. delay, average motor functioning (2) vs. Consistent mild delays(4)			Cog. and motor delays, relative adaptive strength(3) vs. Consistent mild delays(4)		
Covariate	**Coef.(SE)**	**OR(SE)**	**95%CI**	**Coef.(SE)**	**OR(SE)**	**95%CI**	**Coef.(SE)**	**OR(SE)**	**95%CI**
Age, in years	1.968(0.032)**	7.158(0.232)	[6.718, 7.627]	1.66(0.034)**	5.288(0.177)	[4.952, 5.647]	-6.938(0.222)**	0.001(0.000)	[0.001, 0.001]
Sex	0.627(0.038)**	1.872(0.071)	[1.738, 2.017]	0.375(0.033)**	1.455(0.048)	[1.365, 1.552]	0.087(0.042)*	1.091(0.046)	[1.004, 1.185]
Race	0.603(0.039)**	1.828(0.072)	[1.693, 1.974]	0.366(0.034)**	1.442(0.050)	[1.348, 1.542]	0.155(0.045)**	1.167(0.053)	[1.068, 1.276]
Primary language	0.461(0.041)**	1.585(0.066)	[1.461, 1.719]	0.342(0.037)**	1.407(0.052)	[1.309, 1.514]	0.278(0.058)**	1.321(0.077)	[1.179, 1.480]
ASD dx	2.270(0.053)**	9.677(0.516)	[8.717, 10.744]	0.329(0.066)**	1.390(0.092)	[1.220, 1.583]	0.300(0.150)*	1.350(0.202)	[1.007, 1.810]

Note: The coefficients and odds ratios indicate the effect of the covariate in the prediction of membership into the first class listed relative to the reference class. Coef. = regression coefficient; SE = standard error; OR = odds ratio; CI = confidence interval; ASD = autism spectrum disorder; dx = diagnosis ** = significant at the p<.01 level; * = significant at the p<.05 level

Figure 1

Model fit indices from class enumeration

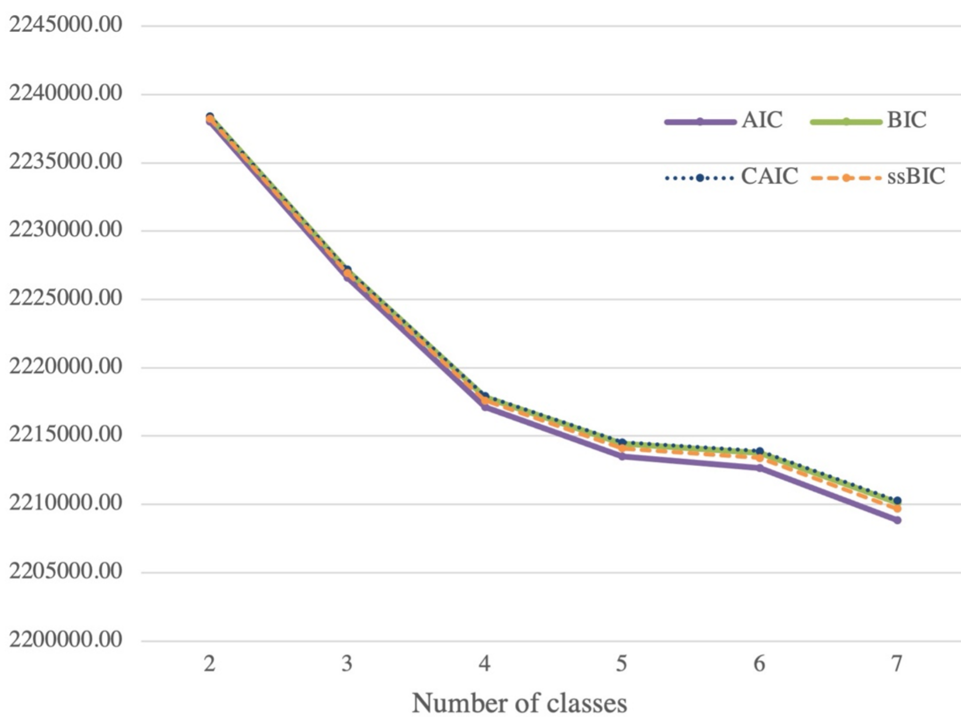


Figure 2

Developmental profiles for the four class-solution (N=57,966)

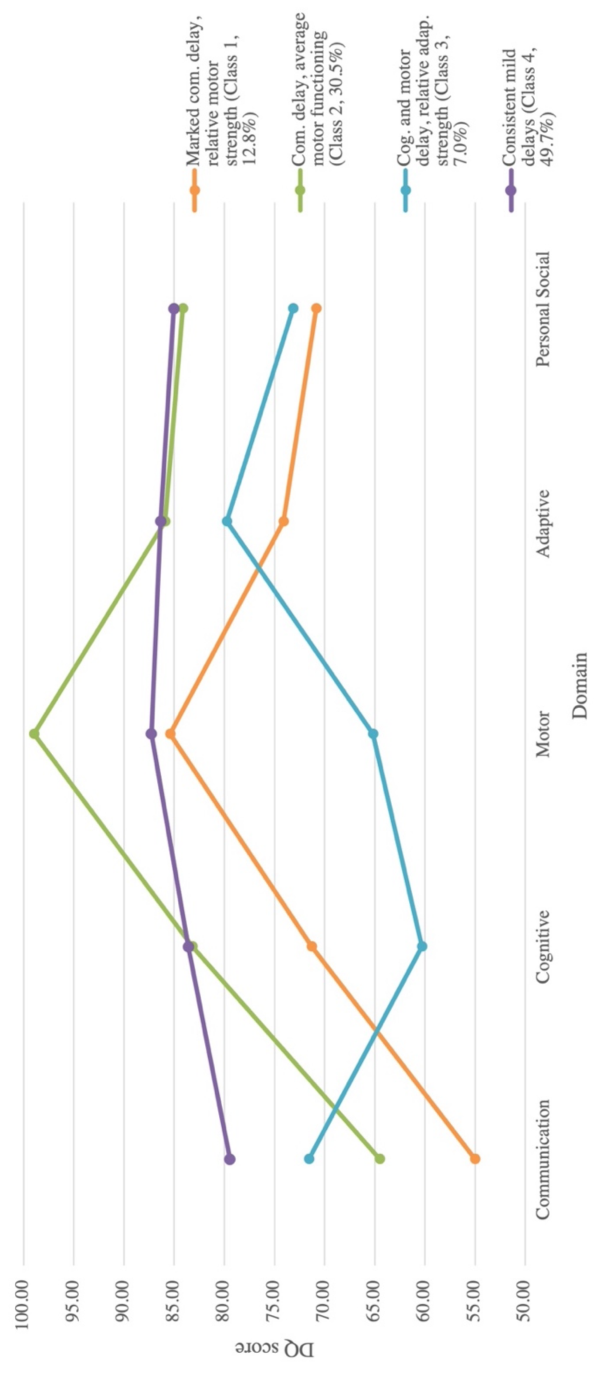
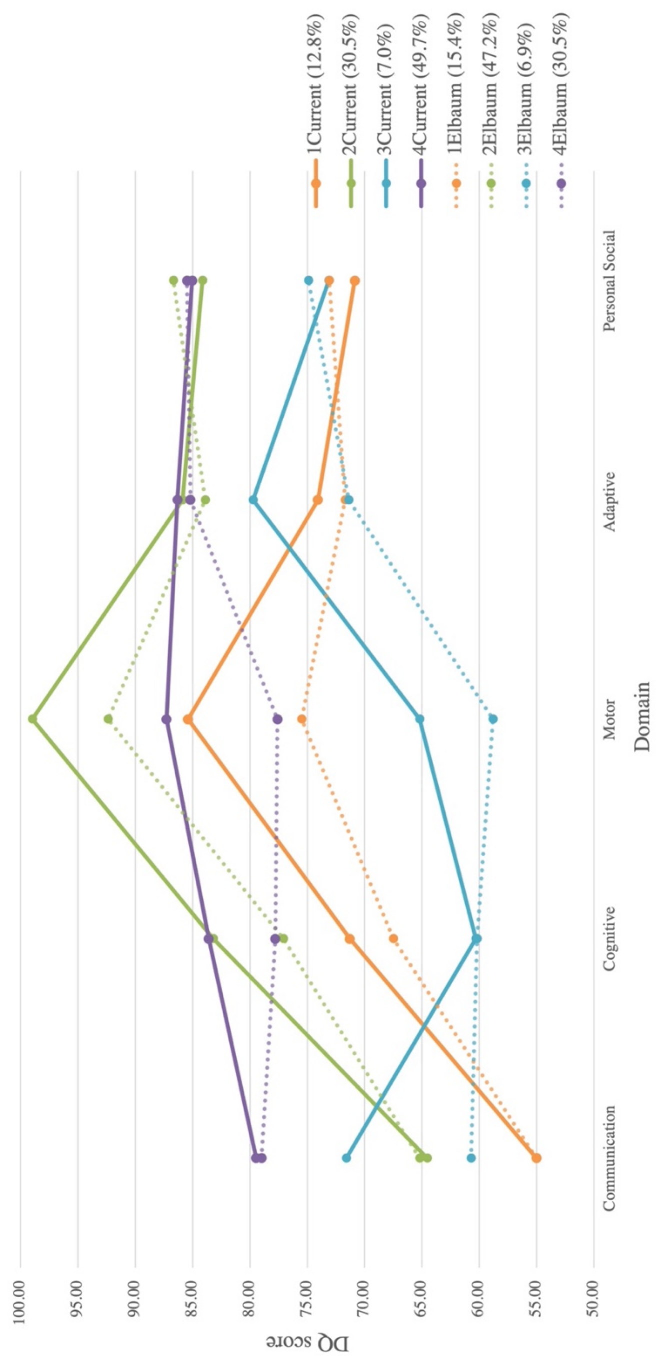
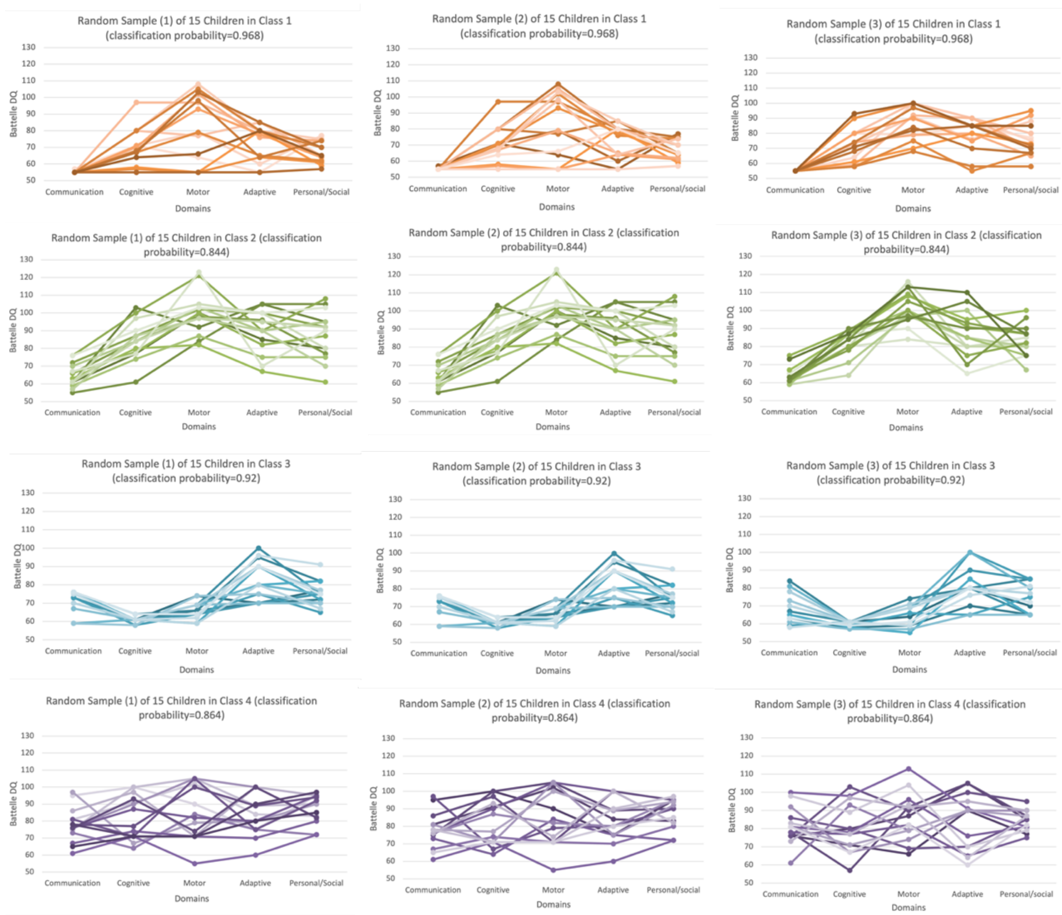


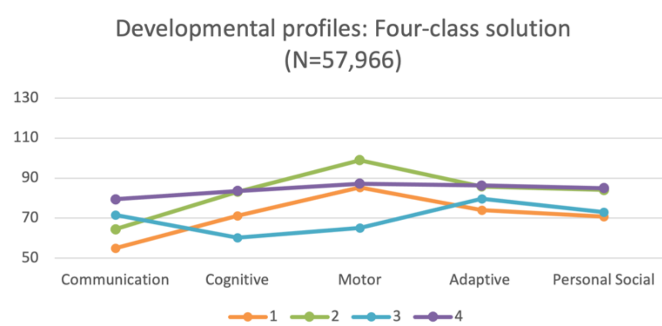
Figure 3

Developmental profiles for the current study's 4-class solution (N=57,966) and Elbaum et al.'s (2017) 4-class solution (N=1,513)



APPENDIX A. RANDOM SAMPLE PLOTS FOR EACH CLASS COMPARED TO OVERALL DEVELOPMENTAL PROFILES.





APPENDIX B. MULTINOMIAL LOGISTIC REGRESSION, WITH INSURANCE STATUS INCLUDED, EVALUATING EFFECT OF PREDICTORS ON LATENT PROFILE MEMBERSHIP.

	(Class 1)Orange vs (4)Purple			(2)Green vs (4)Purple			(3)Light Blue vs (4)Purple		
Covariate	**Coef.(SE)**	**OR(SE)**	**95%CI**	**Coef.(SE)**	**OR(SE)**	**95%CI**	**Coef.(SE)**	**OR(SE)**	**95%CI**
Age, in years	2.160(0.043)**	8.668(0.370)	[7.97, 9.43]	1.838(0.045)**	6.286(0.284)	[5.75, 6.87]	-7.048(0.248)**	0.001(0.000)	[0.001, 0.001]
Sex	0.657(0.044)**	1.929(0.084)	[1.77, 2.10]	0.402(0.038)**	1.495(0.057)	[1.39, 1.611]	0.095(0.046)*	1.099(0.051)	[1.00, 1.20]
Race	0.053(0.048)**	1.922(0.093)	[1.75, 2.11]	0.382(0.041)**	1.465(0.061)	[1.35, 1.59]	0.122(0.052)*	1.130(0.059)	[1.02, 1.25]
Insurance status	0.038(0.413)	1.039(0.048)	[0.95, 1.14]	-0.088(0.040)*	0.916(0.037	[0.85, 0.99]	0.053(0.053)	1.054(0.056)	[0.95, 1.17]
Primary language	0.339(0.049)**	1.403(0.068)	[1.28, 1.54]	0.302(0.044)**	1.352(0.059)	[1.24, 1.47]	0.306(0.063)**	1.358(0.086)	[1.20, 1.54]
ASD dx	2.176(0.058)**	8.814(0.514)	[7.86, 9.88]	0.281(0.072)**	1.324(0.096)	[1.15, 1.53]	0.221(0.152)	1.248(0.190)	[0.93, 1.68]

Coef. = regression coefficient; SE = standard error; OR = odds ratio; CI = confidence interval; ASD = autism spectrum disorders; dx = diagnosis * = p<.05; ** = p<.01

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